An Innovative Power Management Strategy for Hybrid Battery–Supercapacitor Systems in Electric Vehicle

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Article

An Innovative Power Management Strategy for Hybrid Battery–Supercapacitor Systems in Electric Vehicle

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Abstract: Currently, batteries and supercapacitors play a vital role as energy storage systems in industrial applications, particularly in electric vehicles. Electric vehicles benefit from the high energy density of lithium batteries as well as the high power density of supercapacitors. Hence, a robust and efficient energy management system is required to coordinate energy flows between these two storage systems, ensuring road safety. In this study, we develop a novel rule-based strategy called "Continuous Regulation with Dynamic Battery Power Limiting" to establish robust control between the lithium-ion battery and the supercapacitor. A comparative analysis is conducted to evaluate the performance of this proposed approach in comparison to conventional methods. The results show that this approach significantly enhances driving comfort and prevents depletion of the main energy source, resulting in a gain of nearly 30% compared to a lithium-ion battery electric vehicle. Additionally, this new rules-based strategy ensures that the supercapacitor is charged at the end of each drive cycle.

Keywords: electric vehicle with hybrid source; Li-ion battery; supercapacitor (SC); power management system (PMS); Continuous Regulation with Dynamic Battery Power Limiting strategy

MSC: 37M15

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Citation: Jarraya, I.; Abdelhedi, F.; Rizoug, N. An Innovative Power Management Strategy for Hybrid Battery–Supercapacitor Systems in Electric Vehicle. *Mathematics* **2024**, *12*, 50. https://doi.org/10.3390/math12010050

Academic Editor: Nicu Bizon

Received: 3 November 2023
Revised: 20 November 2023
Accepted: 24 November 2023
Published: 23 December 2023

1. Introduction

The transport market, including planes, trucks, and vehicles, is closely linked to fossil resources. Figure 1a shows that nearly two-thirds of energy consumption is oil-based, while 15% is generated from renewable energies. Figure 1b illustrates that "Energy and Electricity" is the primary source of CO_2 emissions, contributing the most significant percentage. Following this, the transport sector, including vehicles, accounts for 24.4% of CO_2 emissions. The World Health Organization has proven that road vehicles emit more air pollution than boats, planes, etc. In particular, gasoline and diesel are the two main sources of water and air pollution. Moreover, it has a dangerous impact on human health, which leads to serious illnesses resulting in a high mortality rate. It is absolutely clear that the unwanted emissions of these petrol vehicles seriously threaten human societies and climate stability [1–5].

This confrontation with the enormous levels of pollution pushes politicians to introduce much more restrictive rules with an increase in taxes on polluting cars. Recently, battery electric vehicles (BEVs) have started to move slightly away from conventional fuels by using cleaner and more sustainable resources [6]. By 2040, countries like China, France, and the United Kingdom (UK) plan to end the sale of petrol and diesel vehicles, while Norway plans to ban polluting cars from 2025 [7,8].

So far, China has remained the undisputed leader in electric mobility, with around 90% of the global vehicle market, while the US market takes second place. Nevertheless, Norway, doing its best on its scale, ranks first in Europe with a market share of 40% [9,10]. Nowadays, this generalization of the clean car first appears as a promising solution. The BEV market kept rising in 2022, with 6.75 million vehicles sold in 2021 in several countries worldwide [11].

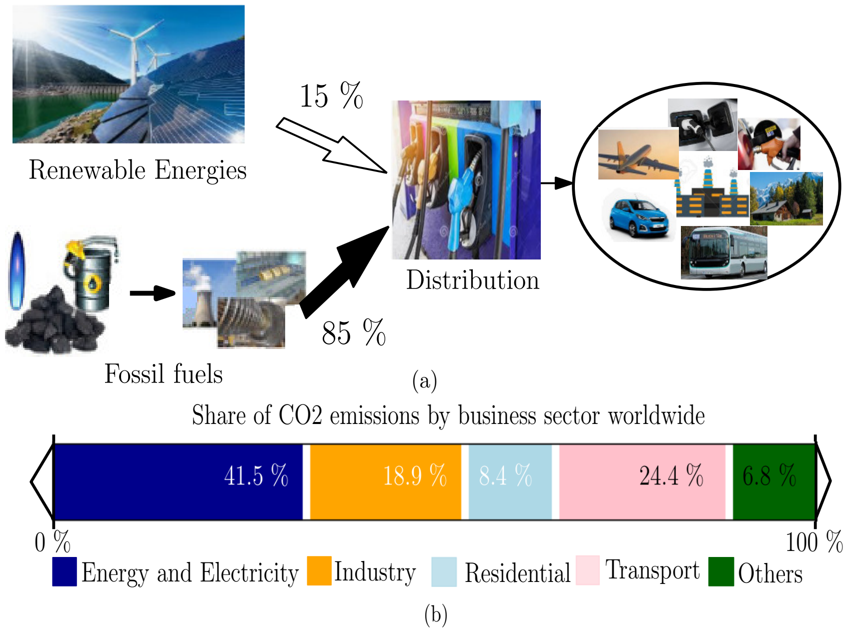

Figure 1. (**a**) The different sources of energy used in the manufacture of automotive fuel; (**b**) share of CO_2 emissions by sector of activity in the world according to the AIE agency.

Therefore, a second transition targeting hybrid-source electric vehicles (HEVs), which consists of a set of energy storage systems (ESSs), may be presented as an alternative solution to improve vehicle autonomy and battery life [12]. This hybridization combines the higher energy density characteristics of the Li-ion battery and the rapid capacity of the SC for energy storage with a virtually unlimited number of charge and discharge cycles [13]. Combining a Li-ion battery primary source with the SC secondary source adds greater HEV range but increases the complexity of the power management system (PMS). Therefore, a compromise between these two important factors should be taken into consideration. Moreover, a good estimation of the state of charge (SOC) of these two energy sources makes it possible to optimize the PMS and the safety of the HEV.

By combining the battery management system (BMS) and capacity management system (CMS) systems, a PMS management system generally gains a higher level of control (see Figure 2). The main function of the PMS is to avoid high ripple currents at low frequency levels, which are susceptible to any heating effect, and to prevent inappropriate use of battery/SC cells. Due to the proposed PMS system, protection against fires and explosions can be ensured throughout the driving of an electric vehicle with a hybrid source. Indeed, it leads to a reduction in battery life.

In this article, we introduce "Continuous Regulation with Dynamic Battery Power Limiting", a novel strategy for effective power management in hybrid electric vehicles (HEVs). This approach represents a significant leap forward in optimizing the interplay between lithium-ion batteries and supercapacitors (SCs), which are vital for the efficiency and durability of HEVs.

Central to the efficacy of our proposed management system is the reliable estimation of non-directly measurable parameters, such as the state of charge (SOC) of the battery and SC. The proposed algorithm critically depends on accurate SOC determinations, alongside measurable inputs like current and voltage. Therefore, we employ a robust extended Kalman filter (EKF) algorithm that integrates open-circuit voltage measurements (OCVs) and recursive least squares (RLS) methods. This hybrid modeling technique ensures an optimal and comprehensive estimation of SOC, pivotal for effective energy management.

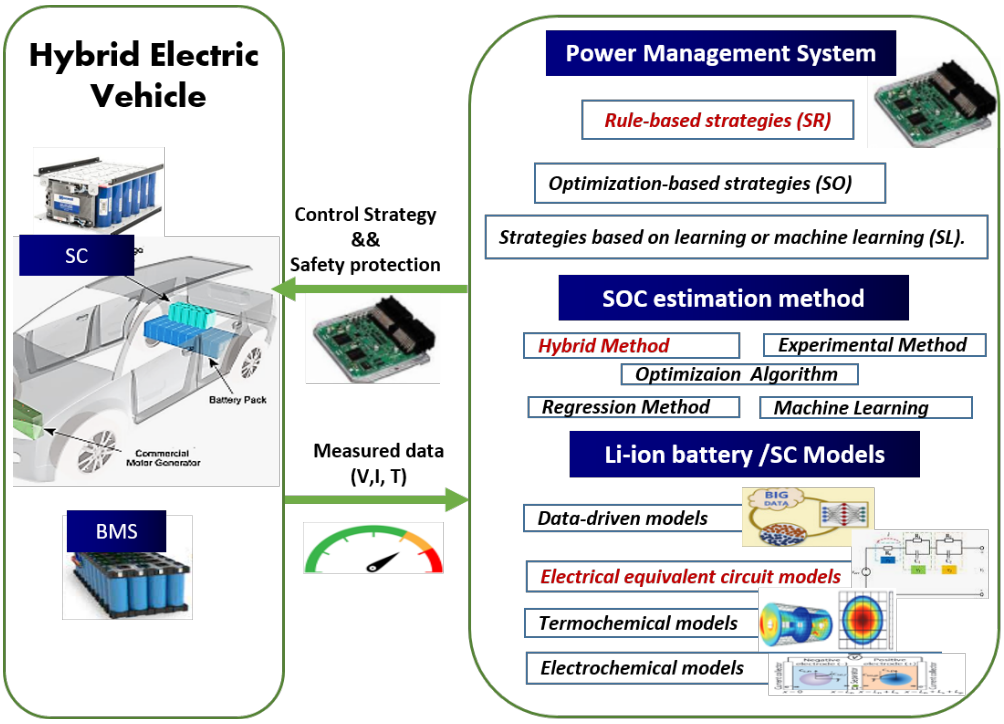

Figure 2. Electric vehicle with hybrid energy source.

Building upon this foundation, our strategy dynamically regulates the energy exchange between the battery and the SC and adapts the battery's current limits based on real-time SOC data. By dynamically adjusting these limits in relation to the SOC of the SC, the proposed concept considerably reduces the operational stress on the battery while optimizing the recharge cycles of the SC. This balance is crucial for maintaining energy efficiency and extending the lifespan of the storage components, especially under varying load and driving conditions.

The practical application and efficiency of the proposed "Continuous Regulation with Dynamic Battery Power Limiting" strategy are substantiated by thorough experimental implementation conducted in real-world driving scenarios. These tests, conducted using an ARTEMIS rolling cycle and a MATLAB-dSPACE interface, validate the strategy's effectiveness in enhancing HEV energy management, paving the way for more sustainable and efficient transportation solutions.

The structure of this paper is as follows: Section 2 delves into the electric vehicle powertrain modeling and various driving cycles. Section 3 presents a comprehensive overview of the current state of energy management strategies. In Section 4, we introduce our novel Continuous Regulation approach with a focus on dynamic power limiting. The experimental setup and results are detailed and discussed in Section 5. Finally, Section 5 concludes the paper with key insights and potential avenues for future research.

2. Electric Vehicle with Battery/SC Energy Storage

2.1. Hybrid Electric Vehicle Dynamics Model

A dynamic model of the vehicle is necessary to properly comprehend how PMS functions and to investigate its impact on the battery/SC energy-storage-based electric vehicles. Figure 3 illustrates the parallel configuration of the studied electric vehicle equipped with both a lithium battery and a supercapacitor.

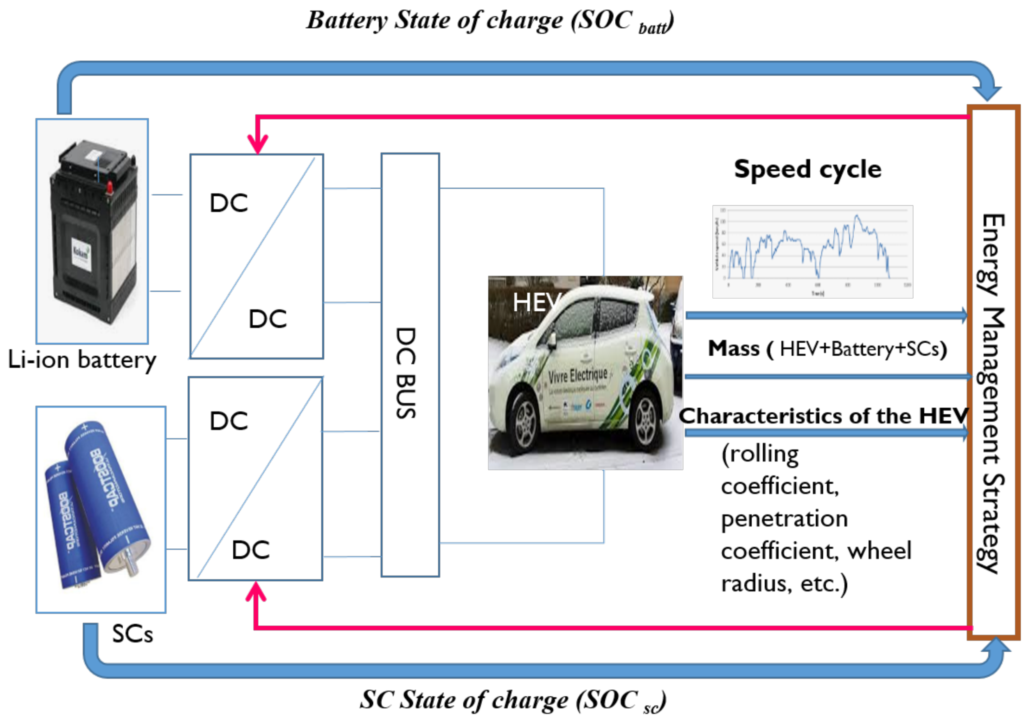

Figure 3. Architecture of the studied electric vehicle with hybrid source

This topology has certain advantages such as independent control of the two storage units with fault tolerance. This vehicle can work even if the failure occurs at the level of one of the converters, which boosts the system's overall reliability.

Using Newton's law of motion [14,15], the expression for the acceleration is given by the following equation:

$$\frac{\partial V}{\partial t} = \frac{\sum F_t - \sum F_r}{\sigma \cdot M} \tag{1}$$

where V is the EV speed; $\sum F_t$ and $\sum F_r$ are, respectively, the EV total tractive force and the resistance forces; M is the EV total mass (motor, storage elements, and body); and σ is the mass factor.

$\sum F_r$, which is expressed by Equation (2), is the sum of aerodynamic force, rolling resistance force, and resistance due to gravity.

$$\sum F_r = F_{aero} + F_r + F_g \tag{2}$$

- Aerodynamic force is given by Equation (3), which is proportional to the square of the vehicle's speed.

$$F_{aero} = \frac{1}{2} \cdot A \cdot \rho \cdot C_x \cdot V^2 \tag{3}$$

where A is the frontal area (m^2), ρ is the density of air (kg/m^2), and C_x is the coefficient of air penetration.

- The rolling resistance force is the resistance force generated by the tire/road contact:

$$F_r = M_t \cdot g \cdot f_r \tag{4}$$

where M_t is the total mass of the vehicle (engine, storage elements, and body), and the rolling resistance coefficient f_r is expressed by Equation (5):

$$f_r = C_0 + C_1 \cdot V^2 \tag{5}$$

- Resistance due to gravity is written in the following form:

$$F_g = M_t \cdot g \cdot \sin\alpha \tag{6}$$

In this work, the characteristics of the "Bollore Bluecar" vehicle are presented in Table 1 [16,17].

Table 1. Characteristics of the electric vehicle studied.

Characteristics	Symbol	Value
Mass	M	1020 kg
Surface	S	2.75 m^2
Maximum speed	V	170 km/h
Air penetration coefficient	C_x	0.3
Rolling resistance coefficient	C_0	0.008
Curve rolling resistance coefficient	C_1	1.6×10^{-6}
Air density	ρ	1.28 kg/m^3

2.2. Drive Cycle

Driving cycles are developed by various organizations to evaluate a vehicle's performance across different criteria, including fuel efficiency, pollutant emissions, and electric vehicle range. Additionally, these driving cycles serve as a means to estimate the efficiency of associated components like internal combustion engines, transmissions, batteries, and electric drive systems.

The New European Driving Cycle (NEDC) has been widely recognized since 1973 as a representation of the vehicle's speed profile over time. However, it was replaced by the World Harmonized Light Vehicle Test Procedure Cycle (WLTP) in September 2017 for new vehicle models. The main distinction is that the outdated normalized cycles consisted of periods of constant speeds and straight acceleration. In contrast, the WLTP incorporates a variety of speed variations. To better reflect real-world performance, transient cycles now utilize real-driving data and provide a more accurate representation of on-road conditions, aligning closely with actual driving scenarios [18].

2.3. Sizing Hybrid Source

The sizing of EVs with hybrid energy storage systems (ESSs) is a complex problem that is difficult to solve using a classical sequential approach. In each dimensioning process, there are strong interactions between the vehicle mission (driving cycle) and its characteristics (mass, surface, air penetration coefficient, curve rolling resistance coefficient, etc.). So, the determination of a certain number of series cells ($N_{s,b}$) or parallel cells ($N_{p,b}$) of the battery and cells ($N_{s,sc}$; $N_{p,sc}$) of the SC must adapt to the real needs of the users and the mission profile of the vehicle.

We developed the hybrid optimization method (algorithm) (PSO/NM) in previous studies, illustrated in Refs. [19–21]. This algorithm succeeded in bringing together the dimension criterion and another effective power criterion in the same objective for a process of identification of the multi-physics model. This then allows the calculation of the number of elements $N_{s,b}$ and $N_{p,b}$ of the battery pack, taking into account the variations in consumption according to the mass of the source.

In order to ensure the vehicle's autonomy, Equation (7) allows determining the necessary values of the battery elements $N_{s,b}$ and $N_{p,b}$, which in turn provide the amount of energy needed to the EV for proper functioning.

$$N_{s,b} \cdot N_{p,b} = \frac{E_{cons}(1 + \sqrt{(1 + 4(E_{max,b}^{el} - 1.4\sigma_E^{cons} \cdot m_b^{el}) \cdot \frac{R_{0,b}^{el}}{U_{min,b}^2}}}{2(P_{disch,b}^{el} - 1.4 \cdot \sigma_E^{cons} \cdot m_b^{el})} \tag{7}$$

where E_{cons} is the energy consumed by the EV, σ_E^{cons} is the variation factor of the energy consumed by the battery as a function of mass, m_b^{el} and $E_{max,b}^{el}$ represent the maximum energy of a battery cell, $R_{0,b}^{el}$ is the internal resistance of a battery cell, and $P_{disch,b}^{el}$ is the maximum power discharge of a battery cell.

So, the main function of the Li-ion battery pack is to store the energy necessary for the vehicle's autonomy, when the SC pack concentrates on the power peaks during acceleration and braking. Therefore, we calculate the energy necessary for the SC to supply and absorb the maximum power in discharge and in charge, taking into account its maximum depth of discharge of 75%. This energy ΔE_{sc} corresponds to the difference between the maximum energy supplied and recovered as follows:

$$\Delta E_{sc} = E_{max,sc} - E_{min,sc} \tag{8}$$

where $E_{max,sc}$ and $E_{min,sc}$ are the maximum and minimum energies stored by the pack of SCs, respectively.

Then, the number of elements $N_{s,sc}$,$N_{p,sc}$ depends on the charge–discharge cycle energy of the SC pack along the driving cycle. Nevertheless, even if the number of SCs cells is calculated with respect to the energy Esc, a verification is carried out with respect to the maximum values of the SC voltage that the sized SCs pack can ensure. Indeed, the voltage of the SC varies between a maximum voltage of the DC bus and a minimum value (almost equal to half of V_{bus}). Therefore, the verification of the constraints imposed on the secondary source is given by Equation (9) as follows:

$$N_{p,sc} = \frac{8\Delta Esc}{3C_{sc}^{el}U_{max,sc}^2} \cdot N_{s,sc} \tag{9}$$

C_{sc}^{el} is the nominal capacity of a SC element, and $U_{max,sc}$ is its maximum voltage.

In this work, we consider that the pack of SCs contains a single parallel branch. Then, the number of elements in series $N_{s,sc}$ is given by Equation (10). The mass and volume clutter indicators of the SC can be calculated in the same way as the main source.

$$N_{s,sc} = \frac{\Delta Esc}{\frac{3}{8} \cdot C_{sc}^{el} \cdot V_{bus}^2 - (\partial_{sc}^{cons} + \partial_{sc}^{rec})1.4m_{sc}^{ele}} \tag{10}$$

where m_{sc}^{ele} is the mass of an element of the SC, ∂_{sc}^{rec} is the power variation factor retrieved from the SC as a function of mass, and ∂_{sc}^{cons} is the power consumption variation factor of the SC as a function of mass m_{sc}^{ele}.

3. Modeling and State of Charge Estimation

The modeling of battery and supercapacitor energy sources in this work takes into consideration technological specifics such as electrochemical processes, internal resistance, self-discharge, temperature sensitivity, and, in particular, charge and discharge characteristics. Furthermore, the fundamental goal is to lay a solid basis and create a simplified model capable of replicating either the battery or the SC behavior in real time for optimal adaptation to EV applications. To achieve these goals, we used models based on equivalent electrical circuits (ECMs) since they provide a good balance of computation time and simulation quality [22].

3.1. Battery ECM Model and Online SOC Estimation

The evolution of electric vehicles has been greatly shaped by the pivotal role of lithium-ion batteries. These batteries have become essential components, driving transformative changes in the world of transportation. Their significance extends across several dimensions, encompassing technological advancements, environmental considerations, market dynamics, and the broader transition toward sustainable and electrified mobility solutions [23]. In the field of battery modeling, various models have been developed to capture the behavior of lithium-ion cells. For instance, the Thevenin model with n-branch (RC) is well suited to Li-ion cells, as exemplified by works such as [24,25]. These models consider the nonlinear and dynamic nature of battery parameters, reflecting changes during charge and discharge cycles, as well as variations in the state of charge (SOC) state.

Thus, Thevenin's model with two branches (RCs) is adopted to model the studied Li-ion battery, as presented in Figure 4 [26]. In fact, Thevenin's model includes four main parts:

- Open-circuit voltage, OCV, which is the potential between the electrodes when the battery is completely disconnected (state of rest or relaxation).
- The internal resistance or the series resistance, R_0, which presents the immediate ohmic voltage drop due to the resistance of electrolyte, pins, and active material.
- The first parallel branch, R_{ct}-C_{ct}, takes into account transient voltages such as double-layer effects and transition effects between ionic and electrical conductance. These transient phenomena have a time constant $\tau 1$ of the order of a few seconds, which is equal to the product of R_{ct} and C_{ct}.
- The second parallel circuit element R_{diff}-C_{diff} considers long-term transient effects as the relaxation effect. The expression $\tau = R_{diff}.C_{diff}$ presents the time constant for these effects, which are on the order of several minutes.

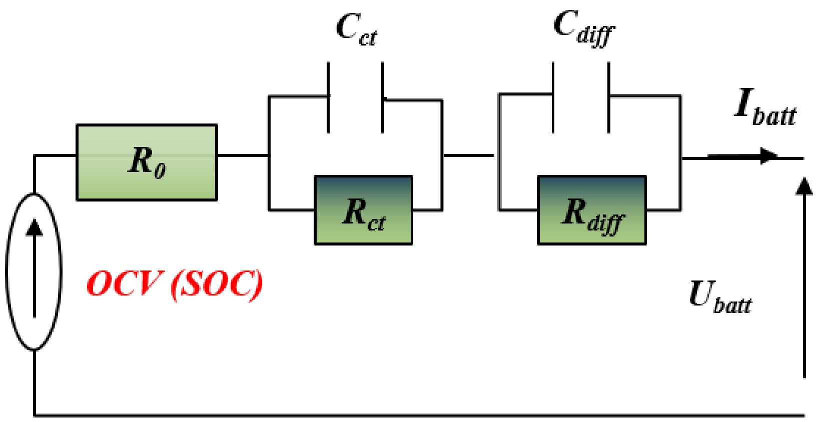

Figure 4. Li-ion battery model.

In this study, the state of charge (SOC) estimation for a Li-ion battery is performed using a robust hybrid estimation algorithm proposed by Jarraya et al. in Refs. [27,28]. This hybrid estimator combines the extended Kalman filter (EKF) and recursive least squares with forgetting factor (RLS) online methods, along with the offline open-circuit voltage (OCV) direct measurement method. The hybrid SOC estimation tool offers several notable features, including real-time online estimation of Li-ion battery parameters (R_0, R_{ct}-C_{ct}, and R_{diff}-C_{diff}) with correction and an update function based on $OCV = f(SOC)$. Additionally, the EKF used in this research demonstrates excellent noise reduction and compensation capabilities, effectively accounting for variations in measurement sensors and acquisition equipment.

The utilization of this hybrid algorithm provides a reliable and accurate approach for determining the SOC of different types of lithium-ion batteries. The average error of the estimated SOC for the battery is less than 0.7%.

3.2. Supercapacitor ECM Model

In this article, the dynamic behavior of the supercapacitor (SC) during charging and discharging phases is simulated using the equivalent circuit model proposed by Rizoug et al. [29], as depicted in Figure 5.

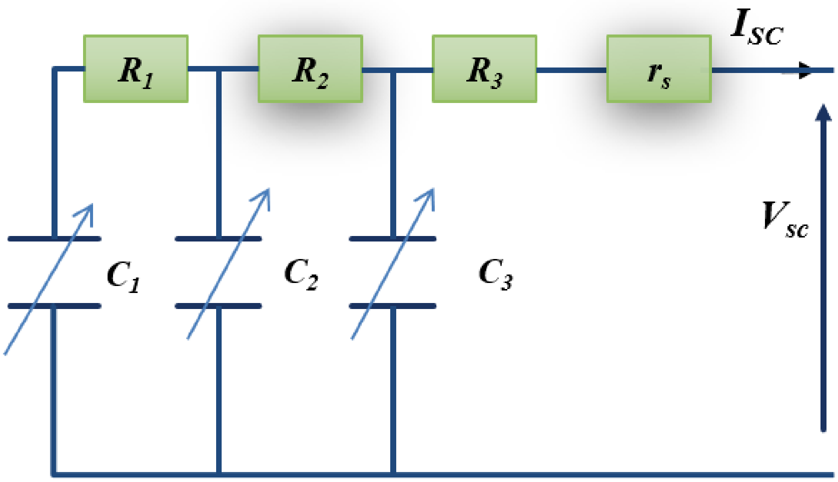

Figure 5. Supercapacitor model.

This model incorporates parallel branches consisting of R_1C_1, R_2C_2, and R_3C_3 to represent the charge propagation resulting from the electrode's surface.

Additionally, the model includes the series resistance r_s, which accounts for joule losses in the metallic conductors and electrolytes, particularly at the activated carbon-collector and collector-contact interfaces. In this study, we have employed the MAXWELL BCAP0350 (2.7 V) supercapacitor technology to enhance the performance of the Li-ion battery.

Temporal characterization with a supercapacitor cell discharge load test may also be used to determine the SC parameters R_1, C_1, R_2C_2, R_3C_3 and r_s. The main idea is to simulate the discharge behavior of the supercapacitor using an RC circuit model, and then fit the model to the experimental data to estimate the values of the model parameters. We may get a set of experimental data by executing a load test and monitoring the voltage and current of the supercapacitor at various intervals. The RC circuit model parameters may then be determined using the system in Equation (11).

$$\begin{cases} R_1 = R_2 = R_3 = 3(R_{\mathrm{LF}} - R_{\mathrm{HF}}) \\ C_1 = C_2 = C_3 = a\, V_{\mathrm{sc}}^2 + bV_{\mathrm{sc}} + c \\ r_s = R_{\mathrm{HF}} \end{cases} \tag{11}$$

where R_{LF} and R_{HF} correspond to the transmission line parameters mainly identified by the frequency characterization. Parameters a, b, and c represent the capacity of the SC adjustment [30].

Simulation results of the SC's thermal response with corresponding experimental results for the same current profile are shown in Figure 6. With this current profile (−50 A/50 A), the SC cell is consecutively charged and drained. In fact, the comparison between both responses shows a small estimation error. The SC model's precision is noticeable.

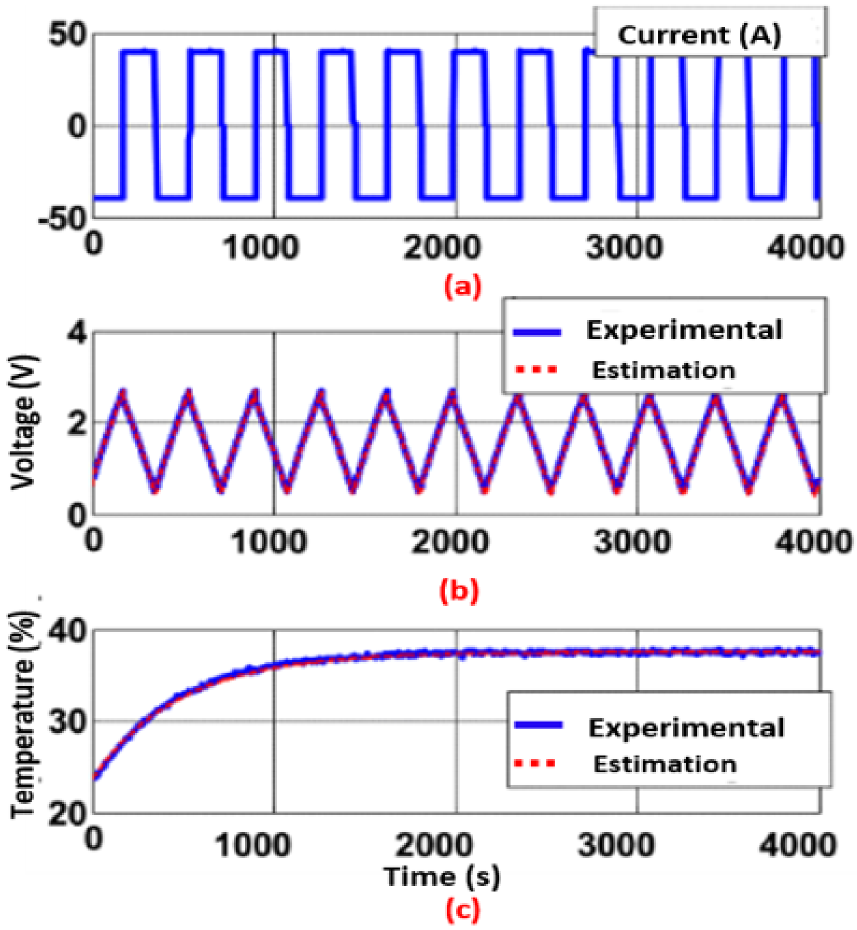

Figure 6. (**a**) Current profile; (**b**) Experimental and modeling SC voltage responses; (**c**) Experimental and modeling SC thermal responses.

4. Active Methods of Energy Management for Hybrid Storage Sources

4.1. State-of-the-Art of Energy Management Strategies

Electric vehicles (EVs) with hybrid storage sources introduce additional degrees of freedom due to the existence of two energy sources coupled with bidirectional converters. Effective management of these sources is crucial and is undertaken by a power management system (PMS). The PMS ensures the vehicle's structural integrity and optimizes the functioning of all resources [31]. It monitors the various components of the EV, controlling energy exchange and determining the optimal power distribution between the energy sources and the load in real time. The primary goal of the PMS is to facilitate efficient switching between different operating modes, thereby enhancing the lifespan and safety of the Storage Systems (SSE).

In recent decades, various strategies have been developed to determine the most appropriate PMS approach in terms of cost, robustness, reliability, optimization, and ease of implementation. Figure 7 provides an overview of these PMS strategies as classified in the literature, which can be broadly categorized into three main approaches [32–36]:

- Rule-based strategies (SR);
- Optimization-based strategies (SO);
- Strategies based on learning or machine learning (SL).

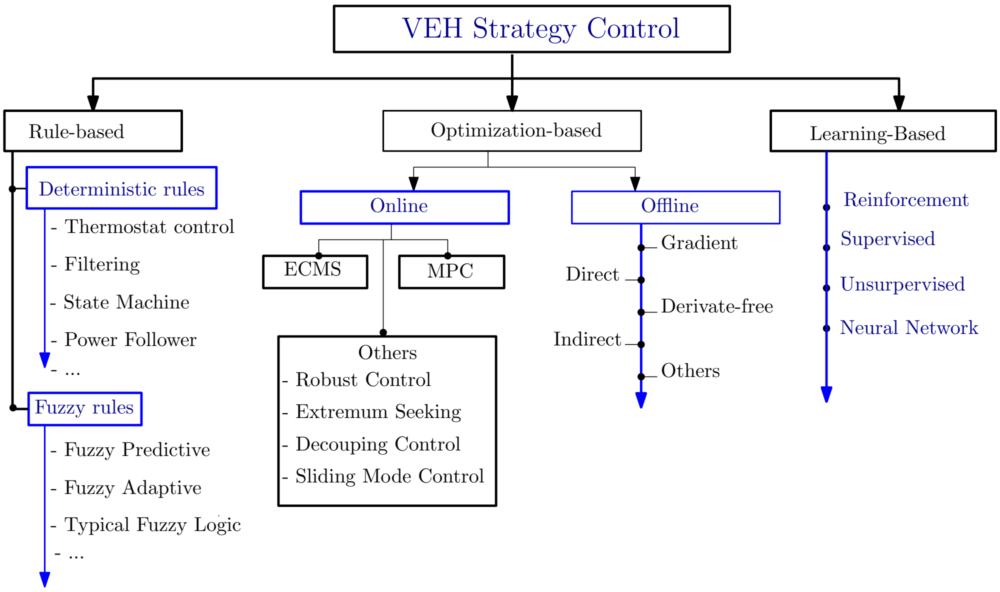

Figure 7. Classification of hybrid electric vehicle (HEV) control strategies [37].

- Rule-based strategies (SR) utilize the expertise of engineers, translating it into executable rules that govern the powertrain's control signals. These strategies are designed to meet specific performance criteria and consider the operational constraints of vehicle components, including the state of charge of energy storage systems (ESSs). SRs are known for their simplicity and effectiveness in real-time supervisory control but may lack adaptability under varying load conditions. This necessitates fine-tuning of vehicle parameters to align with specific performance targets.

Deterministic methods within SR, like the thermostat strategy, manage the SOC through a hysteresis process, alternating between charging and discharging phases. Though robust, they might not account for the entirety of driving scenarios. In contrast, non-deterministic or fuzzy logic approaches within SR offer a more dynamic control mechanism, adept at handling nonlinearities and uncertainties in the vehicle system. The development of these fuzzy systems requires significant expertise in rule formulation and system tuning [38].

- Optimization-based strategies (SO) leverage mathematical models to determine the optimal operational sequence for a system, with the goal of minimizing a specific cost function. This approach is often used to reduce power losses within the hybrid storage system, which can be mathematically expressed as:

$$P_{HSSE,losses} = P_{battery,losses} + P_{SC,losses} + P_{DC/DC,losses} \tag{11}$$

Among the most effective strategies for energy management in such vehicles are ECMS and MPC:

- **ECMS (Equivalent Consumption Minimization Strategy):** In the context of purely electric vehicles, ECMS is adapted to optimize the energy distribution between the battery and the supercapacitor, aiming to enhance overall energy efficiency and prolong the operational lifespan of the energy storage components.
- **MPC (Model Predictive Control):** MPC's role in purely electric vehicles involves predicting future energy requirements and optimizing control actions for efficient energy use. It considers various factors, such as driving conditions and vehicle load, ensuring optimal performance of the electric powertrain.

Despite their theoretical promise, the practical implementation of SOs faces challenges due to the unpredictability of driving conditions and the complexity of the optimization algorithms.

- Machine-learning-based strategies (SL) represent a paradigm shift in power management system (PMS) design for electric vehicles (EVs), bringing data-driven adaptability to energy management. Strategies under the SL umbrella, such as neural networks (NNs), support vector machines (SVMs), and reinforcement learning (RL), learn from historical and live driving data. This learning capability enables the PMS to proactively adjust to changing vehicle demands and driver behaviors.

The efficacy of SL strategies in controlled simulations is evident, demonstrating their potential to significantly enhance energy efficiency and performance. Nonetheless, the application of SL to real-world scenarios is still evolving, primarily due to the "reality gap"—a significant challenge characterized by the differences between simulated training environments and actual vehicle operation.

Bridging this gap involves several key efforts: refining simulation models to more closely mirror real-world conditions, ensuring that behaviors learned in virtual environments translate effectively to physical vehicles, and creating algorithms robust enough to handle the unpredictable nature of on-road driving. These initiatives are crucial for the successful deployment of SL in everyday EV operation, enabling these vehicles to meet the complex demands of modern transportation.

The ongoing development of SO and SL is contributing significantly to advancements in EV energy management. As these technologies evolve, they promise to contribute significantly to the adoption of EVs and the transition towards sustainable transportation ecosystems. According to comprehensive studies by Tran et al. [37], Ali et al. [39], and Vidhya et al. [40], a comparative analysis of various power management system (PMS) algorithms, as depicted in Figure 8, underscores a critical insight: no single strategy currently excels in achieving optimal control objectives for both fuel efficiency and vehicle performance simultaneously. This realization highlights the inherent complexities and trade-offs involved in PMS algorithm design for hybrid electric vehicles (HEVs).

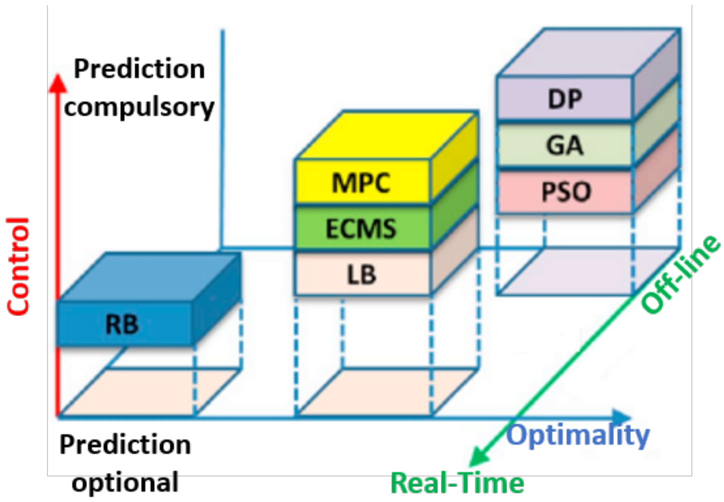

Figure 8. General comparison of power management systems in electric vehicles with hybrid sources (HEVs) [37].

In the context of control strategies for hybrid electric vehicles (HEVs), several optimization approaches are employed, each with its own specific acronym. The following is a list of these acronyms and their corresponding full terms:

- **MPC**: model predictive control;
- **ECMS**: equivalent consumption minimization strategy;
- **LB**: look-ahead control;
- **RB**: rule-based control;
- **DP**: dynamic programming;

- **GA**: genetic algorithm;
- **PSO**: particle swarm optimization.

The challenge with optimization-based strategies (SO) and machine-learning-based strategies (SL) in real-time applications primarily stems from their computational complexity. These strategies often require significant processing time and resources, making them less viable for real-time vehicular control. SO and SL, while theoretically promising, face practical constraints in dynamic vehicular environments. Specifically, SL approaches are contingent upon extensive and often costly datasets that cover a wide range of EV scenarios. The necessity for comprehensive databases and exhaustive testing on real electric vehicles makes the implementation of SL both expensive and demanding in terms of data collection and analysis.

In contrast, rule-based strategies have demonstrated a higher degree of adaptability in real-time scenarios. Their success can be attributed to their straightforward implementation and the ability to quickly respond to varying driving conditions. However, the trade-off for SR is often a reduced capability to optimize for specific performance metrics, such as fuel efficiency, when compared to more complex SO and SL methods.

This comparative evaluation underscores the need for continued research and development in PMS algorithms. A holistic approach that synergizes the strengths of SR, SO, and SL, while mitigating their individual limitations, could potentially pave the way for more advanced and efficient energy management solutions in HEVs.

4.2. Continuous Regulation with Dynamic Battery Power Limiting

Innovative energy management within hybrid electric vehicles (HEVs) necessitates sophisticated strategies for optimal power distribution [41]. Traditional rule-based strategies like the limit method (ML) and filter method (MF) provide a foundation, given their simplicity and ease of real-time implementation.

However, our research represents a significant advancement with the introduction of the "Continuous Regulation with Dynamic Battery Power Limiting" approach. This novel algorithm is centered around the control of the supercapacitor's state of charge (SOC_{sc}). Its primary objective is to dynamically regulate the SOC_{sc}, thereby minimizing the risk of overcharging or deep discharging of the supercapacitor, leading to an enhanced lifespan and reliability.

To provide context and comparison with these traditional strategies, let us briefly outline them:

- **Limiting Method (ML[$Limit_{inf}/Limit_{Sup}$]): **The ML strategy effectively moderates the power or current of the Li-ion battery within a defined range, specified by $Limit_{Sup}$ and $Limit_{inf}$. It ensures that any demand exceeding these limits is accommodated by the supercapacitor (SC_{sc}), striking a balance between battery protection and load requirements.
- **Filter Method (MF[τ_f]): **Operating on an open-loop control scheme, the MF method distributes the power demand across the battery and SC_{sc} using a low-pass filter. High-frequency power requirements are assigned to the SC_{sc}, while the Li-ion battery manages steady, low-frequency demands. This approach effectively mitigates battery stress and enhances response efficiency.

A significant advancement of our "Continuous Regulation with Dynamic Battery Power Limiting" approach is the introduction of a linear relationship between the battery's maximum discharge current and the SOC_{sc}. This relationship, as detailed in Equation (12), plays a crucial role in reducing the battery's operational stress while ensuring efficient recharge cycles for the supercapacitor. This optimization eliminates the need for battery charging during vehicle operation, a critical step in enhancing real-time energy management.

$$I_{\text{batt-disch}} = \begin{cases} I_{\text{batt,max}} & \text{if } SOC_{\text{sc}} < SOC_{\text{sc,min}} \\ a \cdot SOC_{\text{sc}} + b & \text{if } SOC_{\text{sc,min}} < SOC_{\text{sc}} < SOC_{\text{sc,max}} \\ I_{\text{batt,min}} & \text{if } SOC_{\text{sc}} \geq SOC_{\text{sc,max}} \end{cases} \tag{12}$$

Furthermore, we optimize the Li-ion battery's discharge mode through the ML[0/Sup1/Sup2] method. This method showcases two scenarios for variable battery current limitation: one with a range between 5 A and 10 A and another between 3 A and 10 A. These scenarios exemplify our system's adaptability to various power requirements, ensuring efficient and sustainable energy management in HEVs.

5. Validation of Energy Management Strategies

In this section, we explore the various management techniques for our EV hybrid source using the experimental setup shown in Figure 9. Six management techniques are used in this work to assess the viability and effectiveness of our Continuous Regulation with Dynamic Battery Power Limitation improvement strategy. This platform offers foolproof electrical, mechanical, and computer security in any real application of this management to guarantee secure control and coordination between power generation units, converters, and the load.

Figure 9. Experiment test bench in S2ET−Lab in ESTACA−LAVAL.

Control and supervision of the test bench are provided via an interface connection between the dSPACE board and the MATLAB-Simulink board. When the program is launched, the MATLAB-dSPACE interface called the Control Desk allows the input of control and acquisition-related parameters. The graphs also allow one to follow the system's evolution in accordance with the load states of the different sources (SOC_b and SOC_{sc}), the current profiles (Ich, I_b, I_{sc}, I_{emul}, ...), voltage profiles (V_{sc}, V_{bus},...), relays ...etc.

Figure 10 presents the synoptic of the test bench, which is composed of converters, a lithium-ion pack, an SC pack emulator, and another emulator to simulate the charging current of the electric vehicle (see Table 2).

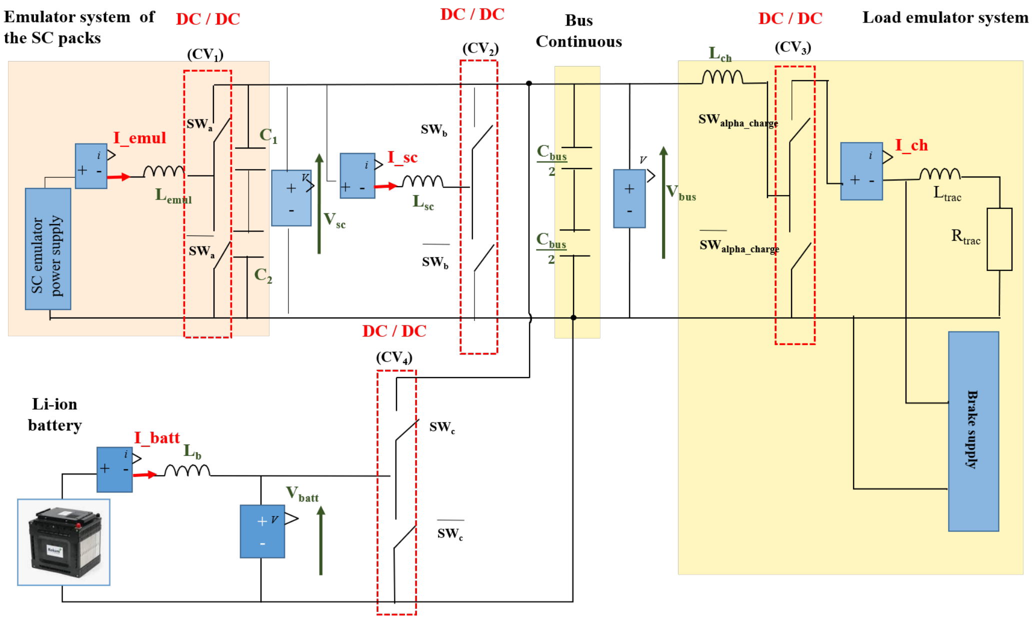

Figure 10. Synoptic of the test bench.

Table 2. General specifications of the different components of the test bench.

PARAMETERS	VALUE
Li-ion battery	Cell Capacity = 15 Ah
Number of cells in series	26 cells
Number of cells in parallel	1 branche
Voltage	95 V
Current (min./max.)	(15/30) A
Supercapacitor	
Number of cells in series	34
Capacity	1000 F
Voltage	92 V
Current (min./max.)	(−40/40) A
DC CONVERTER	
MAXIMAL POWER	6.5 kW
Voltage	200 V
Current (max.)	32 A
BRAKING LOAD (max.)	32 A
TRACTION LOAD (max.)	32 A

This SC emulator, in Figure 11, includes an SC model with control loops to emulate the stable and dynamic SC characteristics in EV applications by reproducing the same voltage/current characteristics of the real battery.

Two converters (CV1 and CV2) are included in the proposed hybrid design to regulate the power exchange between the SC emulator supply and the DC bus. To mimic the behavior of the SC during the load phase, the first converter, CV1, is used. While the discharge phase of the SC will be controlled by the second converter (CV2). On the other side, two bidirectional converters are used to connect the Li-ion battery and charge emulation system to the DC bus (CV3 and CV4). The CV3 converter provides the traction current required by the load, dissipating the power in a resistor. A programmable "brake supply" simulates the braking phase of the process.

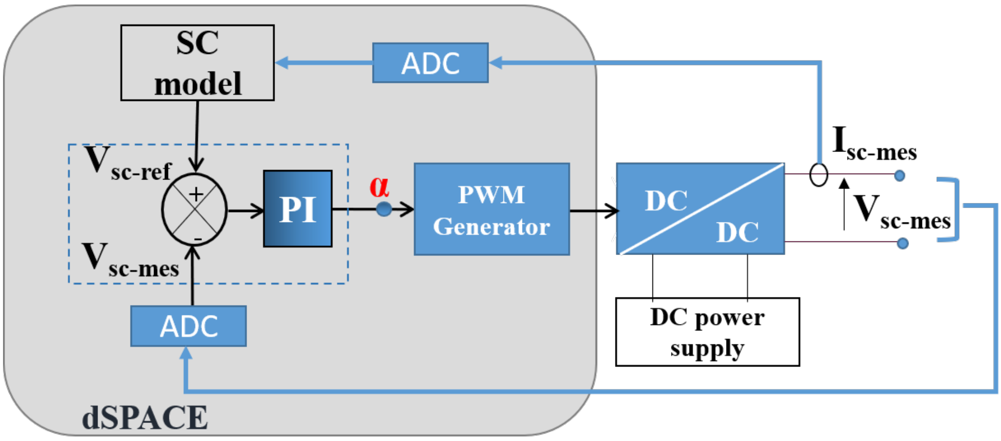

Figure 11. Principle of supercapacitor emulation.

The control of the converters (CV1, CV2, CV3, and CV4) is ensured by the use of "PI" controllers. This study does not address the impact of changing the controller's parameters on system performance. The three converters (CV2, CV3, and CV4) provide the power exchange between the two storage systems and the load for the various operating modes according to a realistic ARTEMIS driving cycle. Utilizing this kind of cycle enables the evaluation of the developed techniques' dynamic response. In the following section, the practical implementation allows comparing and evaluating the different proposed management techniques based on the following criteria:

- Check system security during EV operation.
- Ensure EV braking load and traction satisfaction.
- Maintain DC bus stability around 110 V reference.
- Reduce stress on the battery: The number of charge and discharge cycles a battery may go through before losing its performance is known as cycle life. Besides, the depth of discharge has a considerable impact on the cycle life of Li-ion batteries, as it presents the capacity amount of a battery's storage that is actually being used.

Then, we explore the concept of RMS current I_{eff}, as a performance requirement to be minimized during the rolling cycle, because the life cycle of the ESS depends on its demanding current. Increasing the RMS current generally has negative effects on the ESS and, more importantly, has the potential to accelerate the aging of the Li-ion battery.

The following equation is used to determine the current value.

$$I_{eff}(A) = \sqrt{\frac{1}{T}\int I^2 dt} \tag{13}$$

where, T is the duration of the rolling cycle.

Note: It is important to acknowledge that occasional fluctuations in the signals depicted in the figures are reflective of the genuine variations observed during real-world vehicle driving cycles. These fluctuations arise due to dynamic changes in acceleration, deceleration, braking events, and other inherent characteristics of actual driving scenarios. Additionally, the presence of noise in the measurements, originating from measurement devices, may contribute to certain signal irregularities. Such fluctuations and noise are integral to capturing the true complexity of hybrid energy storage systems' performance within the context of authentic driving conditions.

In the following experimental section, we present the implementation of six key management scenarios: ML[−10A/10A], ML[−8A/8A], ML[−10A/10A] + MF(1s), ML[−8A/8A] + MF(1s), ML[0A/3A/10A] + MF(1s) + SOC_{sc} Control, and ML[0A/5A/10A] + MF(1s) + SOC_{sc} Control. All obtained results are shown in Figures 12 and 18, enabling us to draw the following interpretations and conclusions:

- We implemented the MF strategy with five different values of τ_f (0.01 s, 0.07 s, 0.1 s, 1 s, and 2 s) to assess the impact of the time constant on power sharing between the Li-ion battery and SC. τ_f remains constant throughout the ARTEMIS driving cycle. After experimental implementation, Figure 17 depicts the evolution of the battery's state over time. A comparison of practical results indicates that Figure 17 corresponds to 1 s, leading to a significant reduction in current demands on the battery compared to other time constants, with the lowest battery state of charge.
- The load current, resulting from traction and braking currents, is displayed in Figure 12a,b, respectively. Both figures unmistakably demonstrate that the measured currents closely follow the reference signals due to proper regulation functioning.
- The measured value (in blue) consistently tracks the reference signals (in red) for all adopted management methods (Figures 13 and 14). Each control-command structure proves reliable, robust, straightforward, and easily implementable in a real electric vehicle.
- Experimental testing in Figure 15 illustrates the regulators' efficiency in adapting to load changes and maintaining the required bus voltage of 110.
- Calculation of SC and Li-ion battery effective currents, along with reduction rates for various scenarios, is summarized in Table 3. Note the maximum constraints applied to the battery in the case of a single source (no hybridization), with an effective current of 4.089 A. In EV operation with a single source, the battery experiences charge/discharge peaks, while these peaks decrease by varying percentages for the six management scenarios (EV to hybrid source). Single-source EV operation is more "aggressive" on Li-ion cell packs, leading to a rapid decline in battery life.
- Battery currents shown in Figure 13 reveal that the main source current remains within the limit band imposed by the PMS. The battery's state of charge decreases with current limit reduction, while the effective SC current increases with this band limit reduction, especially in strategies ML[−10A/10A], ML[−8A/8A], ML[−10A/10A] + MF(1s), and ML[−8A/8A] + MF(1s) (see Figures 16 and 17).
- The enhanced approach ML[0/Sup1/Sup2] yields significantly improved battery current with minimal fluctuations. The battery's effective current is lower than Sup1 at 3 A when Sup1 is limited to 5 A (see Table 3).
- Results in Figure 18 exhibit a 27.44% gain (in Ah) in energy exchanged by the battery for the SOC_{sc} regulation method with three battery power variable limits, contributing to longer battery life. Thus, the proposed method demonstrates the supercapacitor's significant role in minimizing battery stress.
- The variable regulation method ensures minimal battery stresses (Table 3), with a 30.18% reduction in stresses compared to the single-phase case. This method also requires the supercapacitor's state of charge to return to the reference value.

Table 3. Effective current

PMS Method	I_{sc-eff} (A)	$I_{batt-eff}$ (A)	Percentage of Stress Minimized Compared to a Single Source
Li-ion battery only	0	4.089	100%
MF(1s)	1.196	3.747	91.63%
ML[−10A/10A]	0.690	3.661	89.53%
ML[−10A/10A] + MF(1s)	1.405	3.553	86.89%
ML[0A/5A/10A] + MF(1s)+ Control SOC_{sc}	1.957	2.893	70.75%
ML[0A/3A/10A] + MF(1s)+ Control SOC_{sc}	1.432	2.854	69.80%

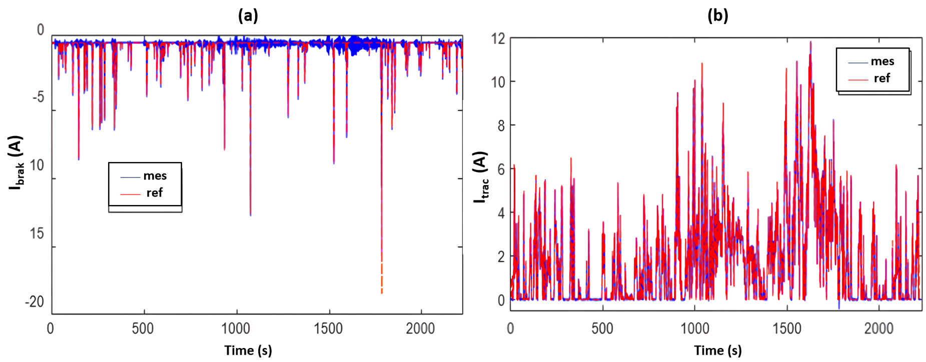

Figure 12. Real and reference current profiles: (**a**)—breaking current and (**b**)—traction current.

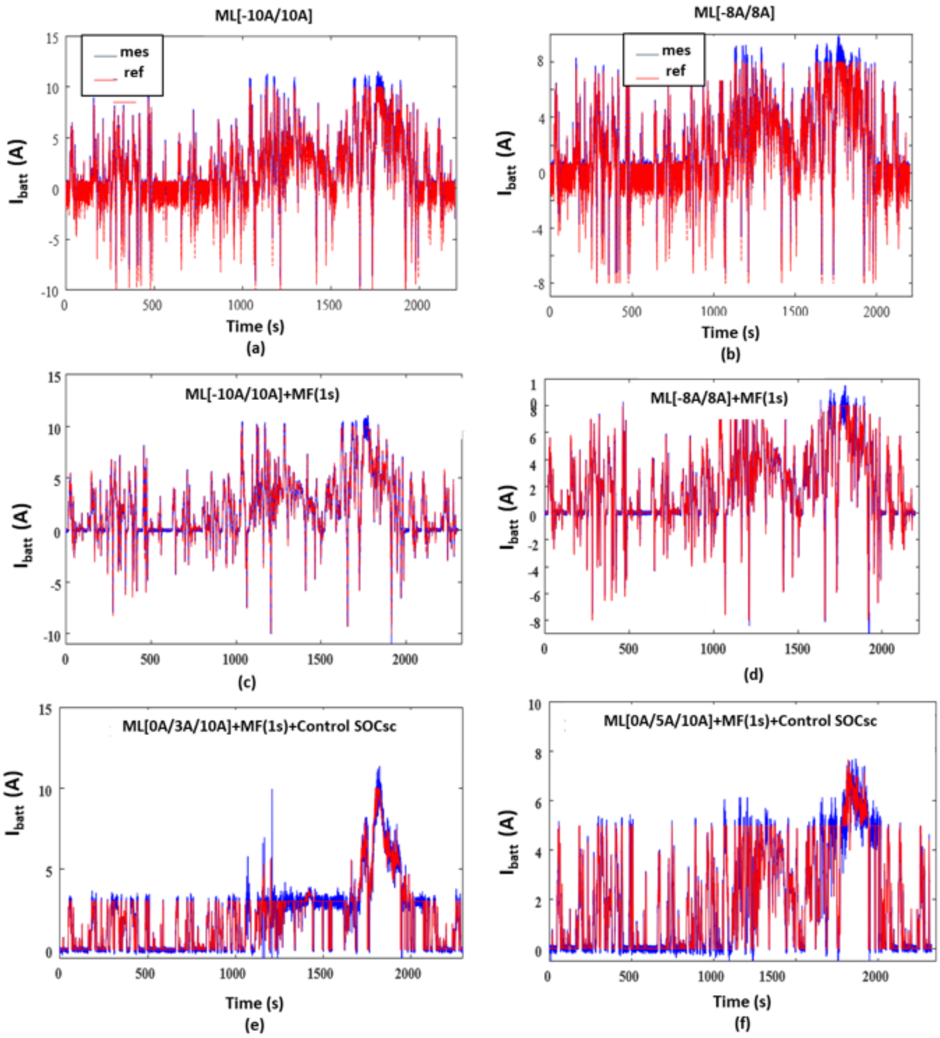

Figure 13. Battery currents (A): (**a**) ML[−10A/10A]; (**b**) ML[-8A/8A]; (**c**) ML[−10A/10A]+MF(1s); (**d**) ML[−8A/8A] + MF(1s); (**e**) ML[0/3A/10A] + MF(1s) + Control SOC_{sc}; (**f**) ML[0/5A/10A] + MF(1s) + Control SOC_{sc}.

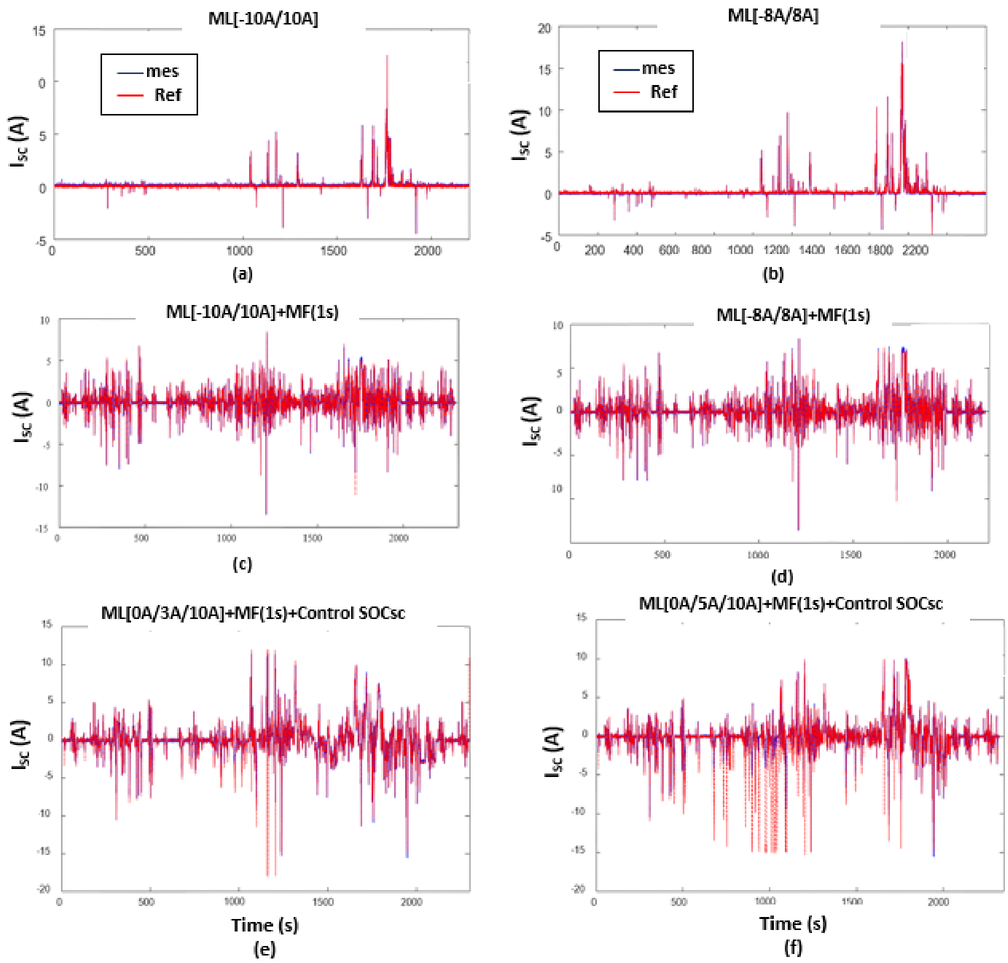

Figure 14. Supercapacitor currents (A): (**a**) ML[−10A/10A]; (**b**) ML[-8A/8A]; (**c**) ML[−10A/10A] + MF(1s); (**d**) ML[−8A/8A] + MF(1s); (**e**) ML[0/3A/10A] + MF(1s) + Control SOC_{sc}; (**f**) ML[0/5A/10A] + MF(1s) + Control SOC_{sc}.

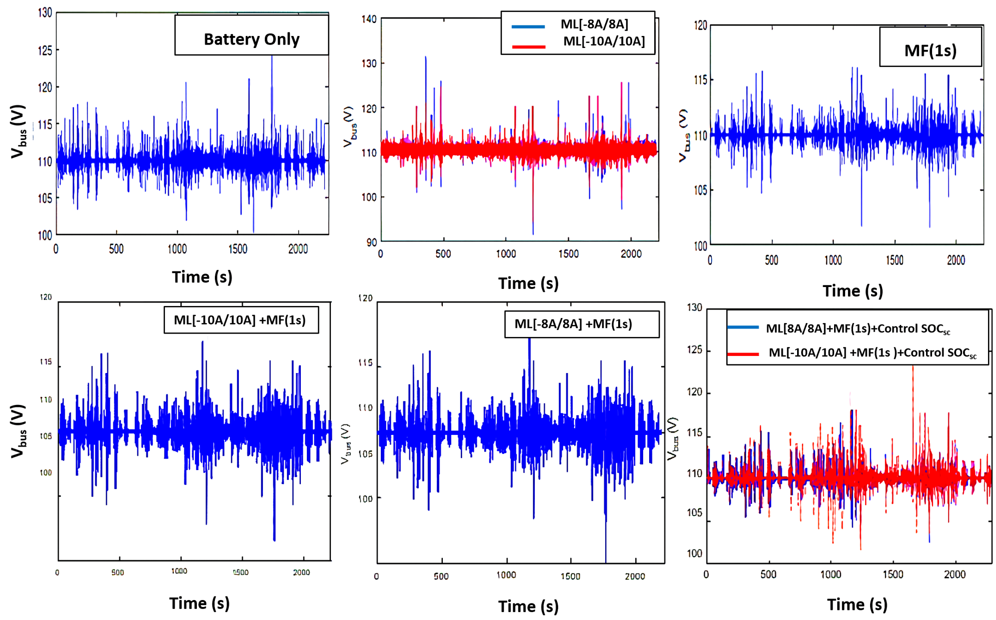

Figure 15. Bus voltage (V).

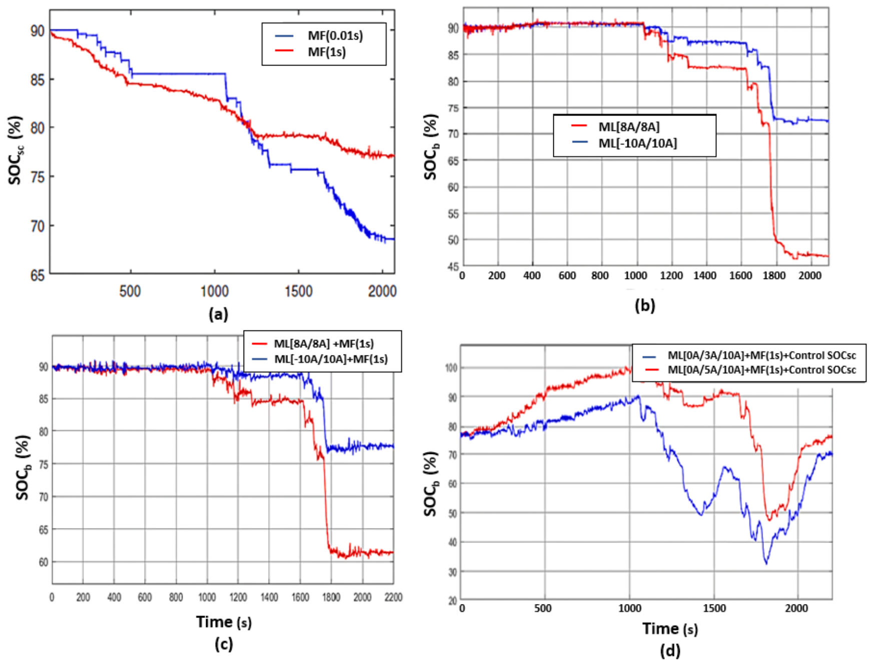

Figure 16. Supercapacitor state of charge.

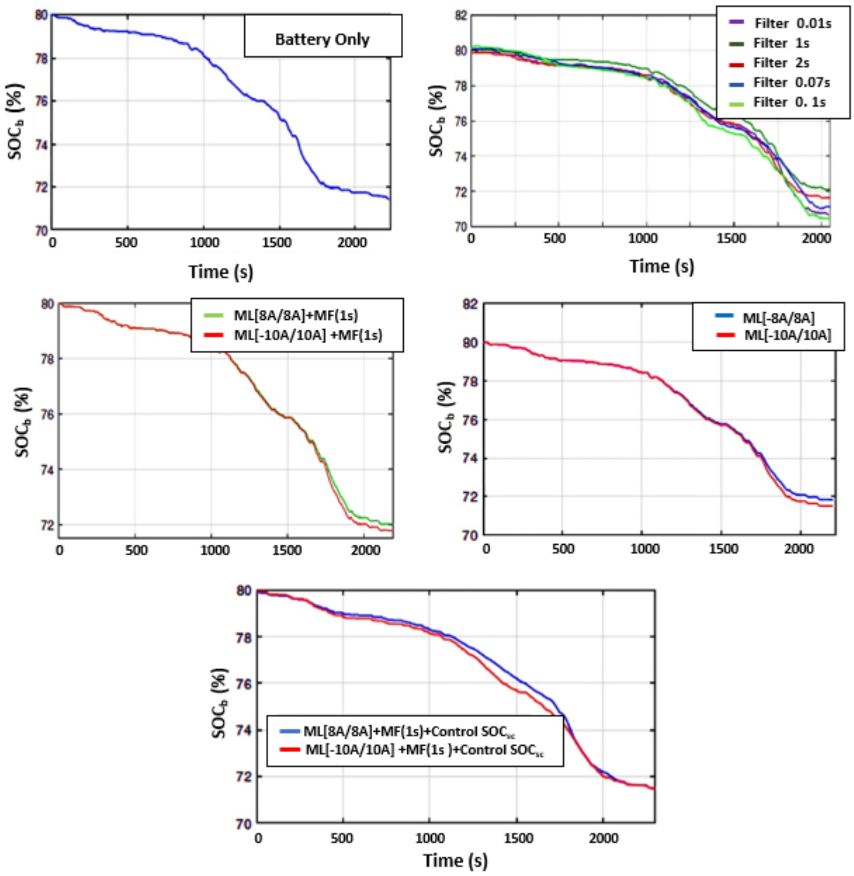

Figure 17. Battery state of charge.

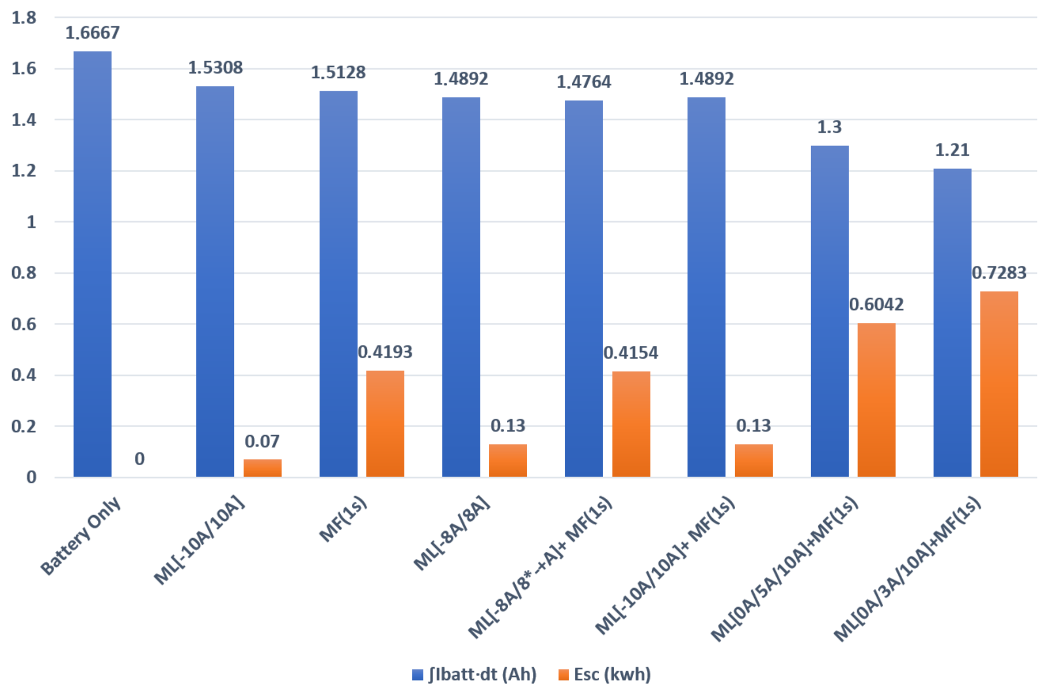

Figure 18. Ratio of the energy exchanged between two storage systems (battery and supercapacitor) in different scenarios.

Our novel approach towards energy management for hybrid energy storage systems in electric vehicles signifies a significant stride in scientific advancement. Within the dynamic landscape of this field, a myriad of strategies have emerged, each aiming to augment performance and efficiency in this specific domain. In this exhaustive comparative analysis, we systematically juxtapose our recently formulated energy management methodology against a diverse array of renowned approaches showcased in various research publications.

In the study titled "Sizing of Lithium-Ion Battery/Supercapacitor Hybrid Energy Storage System for Forklift Vehicle" (Paul, Théophile, et al., 2020) [42], the authors introduce their energy management methodology, which showcases a significant reduction in RMS battery power. Specifically, they elucidate that the RMS battery power can be decreased to 10% in comparison to a single-source solution.

Furthermore, the proposed EMS design in the study titled "Modular Energy Management System with Jaya Algorithm for Hybrid Energy Storage in Electric vehicles" (Demircali, Akif, 2022) [43] aims to enhance the performance of a hybrid energy storage system (HESS)-powered electric vehicle. When comparing the Jaya-based EMS to the rule-based SMS, significant improvements become evident. Specifically, the Jaya-based EMS achieves a substantial reduction of 24.5% in total loss and an impressive 28.8% reduction in the RMS value of the battery current compared to the rule-based EMS.

A compelling comparison can be drawn with the paper titled "CEEMD-fuzzy Control Energy Management of Hybrid Energy Storage Systems in Electric Vehicles" [44] (Shen, Yongpeng, et al., 2023) wherein a fuzzy logic strategy is employed. In contrast to the CEEMD-fuzzy control strategy's reductions of 15.08%, 13.03%, and 21.37% in the RMS value of the lithium-ion battery (LIB) current under different drive cycles, our approach showcases superior performance. Our strategy, remarkably, achieves a more substantial reduction of 30.2%. This notable improvement in reducing RMS battery power serves to further validate the effectiveness of our approach in optimizing battery performance and extending its operational longevity.

6. Conclusions

In conclusion, this research paper highlights the paramount significance of batteries and supercapacitors as fundamental energy storage systems in industrial applications, particularly within the electric vehicle (EV) sector. The synergistic combination of the heightened energy density intrinsic to lithium batteries and the potent power density characteristic of supercapacitors confers significant advantages to EVs. Nonetheless, realizing these benefits mandates the implementation of a robust and efficient energy management system, ensuring both safe operation and optimal functionality.

The study introduces "Continuous Regulation with Dynamic Battery Power Limiting", a revolutionary rule-based technique that is precisely designed to coordinate the complicated interaction of energy flows between the lithium-ion battery and the supercapacitor. This technique aims to improve the overall performance of hybrid energy storage systems in electric vehicles while establishing consistent control. The visible results demonstrate significant improvements in the limiting of the primary energy source's exhaustion. Notably, in comparison to conventional electric vehicles with lithium-ion batteries, a significant 30% advancement has been achieved. Furthermore, the novel rules-based strategy strategically ensures the replenishment of the supercapacitor's charge at the culmination of each driving cycle. This astute optimization of the charging and discharging cadence significantly contributes to the reduction of aggregate battery costs. The cumulative effect of this orchestrated cycle optimization results in enhanced efficiency and extended lifespans for both the lithium-ion battery and the supercapacitor.

From a collective perspective, this research underscores the pivotal importance of astute energy management in the context of hybrid energy storage systems, particularly within the EV domain. The proposed strategy not only promises substantial advantages in terms of energy utilization and financial prudence, but also ushers in a promising era of pioneering advancements in the seamless integration of batteries and supercapacitors. This, in turn, propels the ongoing evolution of environmentally sustainable and high-performance electric vehicles.

Author Contributions: Conceptualization, I.J., F.A. and N.R.; methodology, I.J., F.A. and N.R.; software, I.J. and N.R.; validation, I.J. and N.R.; formal analysis, I.J. and F.A.; investigation, I.J., F.A. and N.R.; resources, F.A.; writing—original draft preparation, I.J. and N.R.; writing—review and editing, I.J. and F.A.; visualization, N.R.; supervision, F.A and N.R.; project administration, N.R.; funding acquisition, F.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research work was funded by Institutional Fund Projects under grant no. (IFPIP: 697-144-1443). The authors gratefully acknowledge the technical and financial support provided by the Ministry of Education and King Abdulaziz University, DSR, Jeddah, Saudi Arabia.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflict of interest.

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